

The evaluation of two management strategies for the Gulf of Alaska walleye pollock fishery under climate change

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Management strategy evaluation (MSE) is the process of using simulation testing with feedback to examine the robustness of candidate management strategies to error and uncertainty. The structure of the management strategy can be selected to attempt to satisfy desired (but conflicting) management objectives. MSE was used to assess the performance of the current management strategy and an alternative management strategy (the “dynamic B_0 ” strategy) for the fishery for walleye pollock (*Theragra chalcogramma*) in the Gulf of Alaska (GOA), when age-1 recruitment was driven by climate. The relationships between age-1 abundance and climate indices (and the uncertainties associated with these relationships) were characterized within an age-structured operating model that was fitted to the data for GOA walleye pollock. Projections into the future were based on the fitted relationships and predictions of those indices from the Intergovernmental Panel on Climate Change (IPCC) models, using the current or the alternative management strategy to determine catch limits. Management performance (the ability to leave the stock close to the management reference level and achieve high and stable catches) deteriorated when age-1 recruitment was forced by climate, although stocks were kept near the reference level on average. In addition, the ability to estimate management-related quantities, such as spawning biomass, deteriorated markedly when recruitment was forced by climate. Performance was sensitive to the choice of IPCC dataset and, in particular, estimation and management performance was poorest (outcomes most variable) for the IPCC datasets that led to the greatest variation in recruitment to the fishery. Although basing management on a “dynamic B_0 ” management strategy led to improved management and estimation performance, the magnitude of the improvement was slight.

Keywords: climate change, Gulf of Alaska, IPCC model output, management strategy evaluation, stock assessment, walleye pollock.

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Introduction

Environmental variability, as it affects marine ecosystems, occurs on multiple spatial (local, regional, basin-scale, hemispheric, and oceanic) and temporal [interannual (e.g. the *El Niño* Southern Oscillation), decadal (e.g. the Pacific Decadal Oscillation, PDO), and long-term (e.g. global climate change)] scales. Many studies have revealed that climate change, climate variability, and regime shifts are associated with fluctuations in fish abundance and population dynamics (Mantua and Hare, 2002), which have important implications for the management of exploited fish stocks (Chavez *et al.*, 2003). However, both the mechanisms related to climate and their effects on changes within ecosystems are poorly understood and even more difficult to forecast (Francis *et al.*, 1998; Dippner, 2006).

There is, however, considerable interest in using relationships between climate indices and annual recruitment processes for fish stocks to improve the performance of management strategies (Myers, 1998). Once correlations between recruitment and climate have been established, they may point the way towards mechanistic explanations of the effects of climate on recruitment. Relationships

between recruitment and climate can be used to increase the accuracy of estimates of historical recruitment and may allow for the short-term prediction of future recruitment.

It might be expected that fisheries management strategies could be tailored to the prevailing environmental state, so that, for instance, the current level of stock productivity is used when estimating biologically allowable fishery removals. For example, the management strategy for the Pacific sardine (*Sardinops sagax*) fishery off the US West Coast uses the average sea surface temperature (SST) at Scripps Pier (La Jolla, CA, USA) during the three preceding seasons to calculate the fraction of the estimated biomass that will be used to set the acceptable biological catch (ABC) for the following year (PFMC, 2007). This management strategy was selected based on simulation studies where the shape of the stock–recruitment curve changed depending on temperature (Anon., 1998). However, for gadoid-like species, Basson (1999) concluded that there was no gain in average yield and progress towards conservation objectives when environmental indices were used for short-term recruitment predictions. When environmental indices were used to alter long-term fishing mortality

Table 1. Climate factors influencing walleye pollock development and survival in the GOA in their first year.

Mechanism	Index	Season	Sign	Reference
Primary production	Precipitation	Winter	+	Bailey <i>et al.</i> (2005)
Primary production	WME	Winter	–	Bailey <i>et al.</i> (2005)
Concentration of prey and larvae	Eddy formation because of freshwater input—precipitation	Spring	+	Kendall <i>et al.</i> (1996)
Concentration of prey and larvae	Upwelling and transport—WME	Spring	–	Kendall <i>et al.</i> (1996)
Stage duration	Temperature	Spring	+	Kendall <i>et al.</i> (1996)
Water column turbulence, eddies, transport, advection, and upwelling	Precipitation	Spring	+	Ciannelli <i>et al.</i> (2004) and Bailey <i>et al.</i> (2005)
Water column turbulence, eddies, transport, advection, and upwelling	WME	Spring and summer	–	Bailey and Macklin (1994), Ciannelli <i>et al.</i> (2004), and Bailey <i>et al.</i> (2005)
Temperature affects the amount of prey and pelagic habitat for juveniles and age-0 animals	SST (may interact with other environmental factors)	Summer and autumn	±	Bailey (2000) and Bailey <i>et al.</i> (2005)

The columns Index and Sign indicate, respectively, observable indices for each mechanism and the postulated direction that increases in the quantity concerned may have on the recruitment of GOA walleye pollock.

reference points, gains were possible if the indices could be predicted in advance accurately, and the links between environmental forcing and recruitment were robust and well-defined (Basson, 1999). De Oliveira and Butterworth (2005) evaluated the use of environmental indices of recruitment in developing management strategies. Consistent with the findings of Basson (1999), they found that there were limits to the benefits of including such indices in management strategies, unless they could account for at least 50% of the total variability in recruitment.

Walleye pollock (*Theragra chalcogramma*) is a member of the family Gadidae, which includes cods and haddocks. It is a semi-pelagic schooling fish distributed in the North Pacific Ocean, primarily above 40°N. Spawning occurs in February and March for the stock of walleye pollock in the Gulf of Alaska (GOA). The age-at-50% maturity for GOA walleye pollock is 4.9 years and GOA walleye pollock live to at least age 15 years (Dorn *et al.*, 2005). Long-term trends and changes in the productivity of walleye pollock appear to have been influenced profoundly by climate change, environmental variability, and regime shifts (Jurado-Molina and Livingston, 2002). Regime changes in the North Pacific Ocean in 1977 and 1989 (Hare and Mantua, 2000) are also believed to have affected the composition of the GOA ecosystem (Anderson and Piatt, 1999).

Recruitment success of walleye pollock in the GOA has been postulated to be related to several effects of climate (Table 1; Figure 1). For example, it has been hypothesized that the seasonal effects of precipitation, wind-mixing energy (WME), and transport in the Alaska Coastal Current and ocean water advection near Shelikof Strait affect walleye pollock recruitment (<http://www.pmel.noaa.gov/foci/forecast/06.pdf>; Dorn *et al.*, 2006). Specifically, it has been proposed that high levels of precipitation can lead to more eddies, which are thought to be beneficial for the survival of early life-history stages (Bailey *et al.*, 2005). High levels of WME during winter are hypothesized to lead to greater survival of eggs and larvae, because of entrainment, and of early juveniles owing to increases in offshore plankton assemblages (Bailey *et al.*, 2005). In contrast, high levels of WME and advection in spring and early summer can lead to greater turbulence and mixing in the water column, which is thought to affect negatively larval and juvenile feeding, transport, and survival (Bailey and Macklin, 1994; Ciannelli *et al.*, 2004). An interaction between

SST and WME has also been postulated (Bailey *et al.*, 2005), in that low SST and high winds may lead to decreased survival.

A directed foreign fishery for walleye pollock in the GOA began in 1964, which transitioned to a fully US domestic fishery in the mid-1980s (Dorn *et al.*, 2005). It is the second largest directed fishery in the GOA, with annual catches between 50 000 and 120 000 metric tonnes (t) since 1986 (Dorn *et al.*, 2005). The fishery is managed by the National Marine Fisheries Service (NMFS), based on recommendations from the North Pacific Fishery Management Council (NPFMC). The management strategy used for the GOA walleye pollock fishery is the “Tier 3 harvest control rule” (NPFMC, 2006). This management strategy uses a constant fishing mortality rate that decreases linearly when the stock is assessed to be below a reference level of spawning biomass. Since 2002, the NPFMC has consistently adopted measures that reduce the ABC recommendation from the Tier 3 harvest control rule to provide greater protection against assessment uncertainty when the stock drops below reference levels (Dorn *et al.*, 2001).

In this study, we considered the effects of climate change on the productivity of the GOA walleye pollock stock through fluctuations in age-1 abundance within a management strategy evaluation (MSE; Smith, 1994) framework. This differs from previous work (A’mar *et al.*, 2008), in that it combined quantifying hypotheses about the effects of climate change on the walleye pollock stock and evaluating the responses of the current and an alternative management strategy to those effects. The objective was to assess whether the two management strategies, which are both based on dynamic feedback, were robust to variations in age-1 abundance caused by the climate effects on GOA walleye pollock. In contrast to previous studies, the primary aim of this study was not to provide support for any of the mechanisms through which climate change would act, but rather to assess which (if any) of them (if correct) would lead to undesirably poor performance of the management system, and, if so, to evaluate the degradation in performance.

Methods

MSE, which is also referred to as management procedure evaluation (De la Mare, 1986), involves testing of a management strategy using simulation, and summarizing the results using

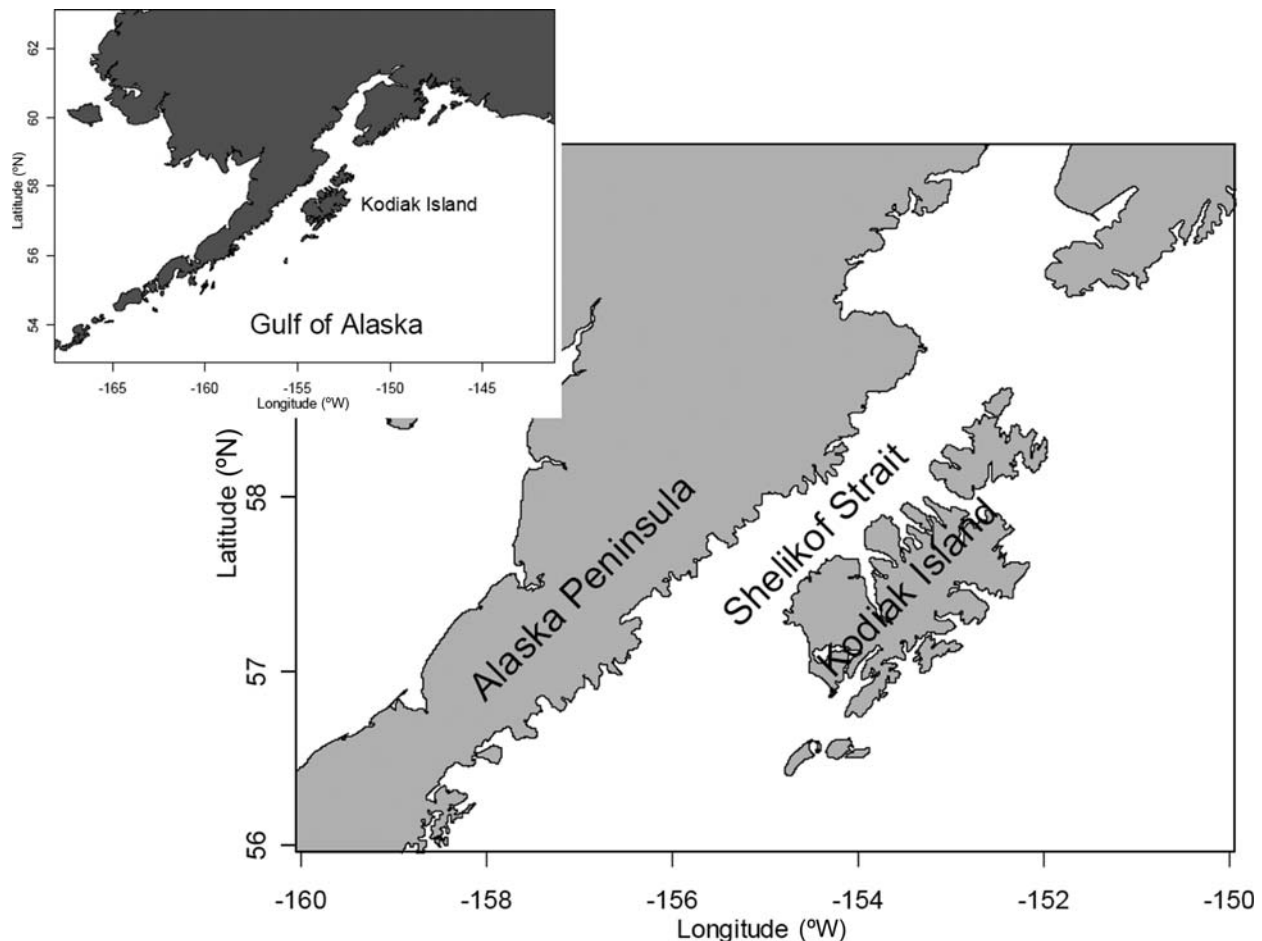


Figure 1. The GOA (inset), and Kodiak Island and the Shelikof Strait area.

performance measures to determine how effective the management strategy is at achieving fishery management goals, given uncertainty (Smith, 1994). The components of an MSE are an operating model, which represents the true dynamics of the stock through time and generates the data to be used by the management strategy, the management strategies to be evaluated, and a set of performance measures that are determined from the management goals. The operating model is used to subject the management strategy to assessment error, uncertainty, and hypotheses regarding the link between climate and recruitment during a projection period.

In this study, historical environmental indices were used to quantify the effects of potential climate-induced mechanisms on age-1 abundance of GOA walleye pollock. The performance of the management strategies was therefore evaluated given a relationship between climate and age-1 abundance. The stock assessment data used in this study were those available as of 1 January 2006, so the start year of the simulations was 2006. The end year of 2050 was chosen, because the datasets from the Intergovernmental Panel on Climate Change (IPCC) climate models are argued to be reasonable for the first half of the twenty-first century, but the projections of the forcing mechanisms are not as clear for the latter half (IPCC, 2007a). The stock, the influences of climate, and the management strategy were projected forward with feedback annually over the 45-year period 2006–2050 by

forcing age-1 abundance based on the values for the future climate indices (datasets from IPCC climate models).

Data

The data for the projection models of age-1 abundance for walleye pollock were based on the relationship(s) used by Dorn *et al.* (2006) to make forecasts of recruitment, and those factors postulated by Bailey *et al.* (2005), Bailey and Macklin (1994), and Ciannelli *et al.* (2004) to influence age-1 abundance. The data used in the projections were restricted to those data sources that can be forecast into the future [Dorn *et al.* (2006) make forecasts for recruitment based on larval counts and stock assessment model estimates of age-2 recruitment, as well as precipitation, WME, and advection of ocean water near Shelikof Strait. Data on advection are not available for the entire period of the fishery, and larval counts cannot be predicted into the future (except as being related to spawning biomass, but that relationship is very weak; Dorn *et al.*, 2006).]:

- (i) The monthly precipitation on Kodiak Island, Alaska, for January 1962 through December 2005 [S. Allen Macklin, NOAA/Pacific Marine Environmental Laboratory (PMEL), pers. comm.].
- (ii) Monthly WME at 57°N 156°W estimated from sea-level pressure analyses for January 1962 through December 2005

Table 2. Correlations between the historical seasonal climate indices (1962–2005).

		Winter			Spring			Summer			Autumn		
		Precip	WME	SST	Precip	WME	SST	Precip	WME	SST	Precip	WME	SST
Winter	Precip	1.0											
	WME	–0.347	1.0										
	SST	0.671	–0.309	1.0									
Spring	Precip	0.249	–0.071	0.010	1.0								
	WME	–0.389	0.428	–0.271	–0.098	1.0							
	SST	0.547	–0.364	0.695	0.001	–0.581	1.0						
Summer	Precip	0.046	–0.050	0.045	0.007	–0.093	–0.105	1.0					
	WME	–0.063	0.195	–0.110	0.208	0.394	–0.105	0.048	1.0				
	SST	0.446	–0.212	0.530	0.099	–0.659	0.832	–0.033	–0.124	1.0			
Autumn	Precip	0.294	–0.181	0.108	0.206	–0.296	0.170	–0.005	–0.186	0.246	1.0		
	WME	–0.237	0.296	–0.121	–0.162	0.425	–0.278	–0.061	0.410	–0.406	–0.379	1.0	
	SST	0.511	–0.180	0.494	0.254	–0.273	0.578	–0.048	0.104	0.615	0.383	–0.377	1.0

The italicized values indicate correlations (ρ) between 0.4 and 0.5 in absolute terms, and the emboldened values indicate correlations >0.5 in absolute terms. “Precip” is precipitation, “WME” is wind-mixing energy, and “SST” is sea surface temperature.

(S. Allen Macklin, pers. comm.). The data are in units of watts m^{-2} , converted to $\text{m}^3 \text{s}^{-3}$ to match the outputs from the IPCC models by dividing by the density of air at sea level at 0°C , 1.293 kg m^{-3} .

- (iii) Monthly SST in $^\circ\text{C}$ at 55°N 157°W , which is down-current from Shelikof Strait, for January 1960 through December 2005 (ICOADS 2° Enhanced SST from <http://www.cdc.noaa.gov/icoads-las/servlets/dataset>).

The environmental data were calculated for the Kodiak Island/Shelikof Strait area (Figure 1), because the Shelikof Strait has historically been one of the main spawning areas for walleye pollock in the GOA (Bailey *et al.*, 2005).

The time-series for each of the three climate indices (precipitation, WME, and SST) were averaged over four 3-month seasons to form indices for winter (January, February, and March), spring (April, May, and June), summer (July, August, and September), and autumn (October, November, and December), resulting in the 12 seasonal climate indices used in the analyses. The seasonal climate indices are correlated with each other (Table 2), and represent periods that reflect the physical environment and biological conditions before and during spawning, and survival during the post-larval and early juvenile stages (Table 1). The historical seasonal climate indices, “ $CI_{i,y}$ ”, were normalized by calculating the mean, \bar{I}_i , and standard deviation, s_i , for each seasonal climate index i and defining the normalized indices, “ $I_{i,y}$ ”, as $(CI_{i,y} - \bar{I}_i)/s_i$. Consideration was also given to including the monthly PDO index in the analyses, but this was not pursued, because the PDO anomaly time-series is highly correlated with SST ($r_{\text{winter}} = 0.788$; $r_{\text{spring}} = 0.691$, $r_{\text{summer}} = 0.417$, $r_{\text{autumn}} = 0.595$).

The predictions of precipitation, WME, and SST, on which the operating model projections of age-1 abundance were based, were obtained from the downscaled output of six IPCC general circulation models (Table 3). These models produced results for the Northeast Pacific Ocean for the period January 2001 through December 2050 [provided by Nicholas Bond and Muyin Wang, University of Washington Joint Institute for the Study of the Atmosphere and Ocean (UW/JISAO)] and were selected for both their accuracy with respect to the historical data and their predictions with respect to future climate scenarios (Randall *et al.*, 2007). The climate indices forecast using these models

Table 3. The eight datasets [from the World Climate Research Programme (WCRP) CMIP3 multi-model dataset] from the six IPCC general circulation models (IPCC, 2007b).

Model	Source	Abbreviation
CCSM3.0	National Center for Atmospheric Research, USA	ccsm31
GFDL 2.0 and 2.1	NOAA/Geophysical Fluid Dynamics Laboratory (GFDL), USA	gfdl201, gfdl211
MIROC3.2, High and Medium Resolution	The Center for Climate System Research/National Institute for Environmental Studies/Frontier Research Center for Global Change, Japan	mirocH1, mirocM1, mirocM2, mirocM3
UKMO-HadCM3	The Meteorological Office/Hadley Centre for Climate Prediction and Research, UK	ukhadcm31

represented local-, regional-, and basin-scale processes in the GOA and were used for the 45-year projection period, 2006–2050. Specifically, these six models were in the subset of models that replicated the spatial pattern and temporal characteristics of the first principal component of SST in the North Pacific Ocean (the PDO) observed in the latter half of the twentieth century. For some variables, such as SST and precipitation, the information used was direct model output. For the wind mixing, predictions were based on empirical relationships that have been established using direct measurements for mixing and large-scale pressure patterns (which are available from the twenty-first century forecasts from the general climate models, GCMs; IPCC, 2007b). The forecasts used are based on the moderate A1B emissions scenario, which assumes that, over 2000–2100, the world population increases slowly, economic growth is rapid, and new and more efficient technology is introduced, resulting in decreasing methane and nitrous oxide emissions and increases in other greenhouse gas emissions (IPCC, 2007b). In general, the GCM forecasts are not highly sensitive to the assumed emissions scenario for the first half of the twenty-first century, but this sensitivity becomes

Table 4. The climate indices selected for inclusion in the operating models, the negative log likelihoods (NLL) for these operating models, the number of parameters estimated in each model, and their AIC values.

Model	Precip–Win	SST–Spr	Precip–Sum	SST–Sum	SST–Aut	NLL	# Param	AIC	ΔAIC
Base	–	–	–	–	–	1 309.82	307	3 233.64	116.18
Model 1						1 246.73	312	3 117.46	0.00
Model 2			–			1 247.80	311	3 117.60	0.14

"|" indicates that the index is used in a model. Model 2 is nested within model 1. See Appendix for more details.

substantial for the latter half of the century. The GCM simulations comprise a set of individual runs, so are formally independent, but do share commonalities in terms of model architecture and parameterizations as well as in the forcing associated with assumed trace gas concentrations.

Including effects of climate on future recruitment success

The operating model represented the “true” state of the resource, and incorporated hypotheses regarding how the age structure of the resource changed through time. The operating model was age-structured, projected both age-1 abundance and spawning biomass, and included several process and observation error terms (A'mar *et al.*, 2008). It was similar in structure to the population dynamics model on which the 2006 GOA walleye pollock stock assessment (Dorn *et al.*, 2006) was based, primarily because this was the most recent assessment when the analyses of this paper were conducted. The main differences between the operating model and the original stock assessment model were that the operating model used a linear combination of seasonal climate indices to account for some of the variation in age-1 abundance and the operating model covered ages 1 through 15 years, whereas the stock assessment model covered ages 2 through 10 years.

The operating model was conditioned on historical fishery, survey, and environmental data. Conditioning was achieved using a Bayesian estimation approach [Markov chain Monte Carlo (MCMC); Hastings, 1970; Gelman *et al.*, 2004], which led to a posterior distribution for the values of the parameters of the operating model (e.g. coefficients for the seasonal environmental indices, historical recruitment, historical fishing mortalities, survey catchability, fishery and survey selectivity parameters, etc.). Each future year of the 45-year projection period involved: (i) using the operating model to generate the survey and fishery data used by the estimation model component of the management strategy; (ii) applying the management strategy to determine a catch limit; (iii) determining the consequences of the catch limit on the population represented in the operating model; and (iv) generating future recruitment based on the relationship between age-1 abundance and the IPCC climate indices. In the projections, the recruitment process error, and the observation error applied to the “true” survey indices of abundance, survey catch proportions-at-age, and fishery catch proportions-at-age, was temporally uncorrelated. For the purposes of this study, 100 simulations, each of which was based on a different draw from the Bayesian posterior distribution, were conducted for each operating model. Implementation error was not considered in this study.

Some of the fluctuations in estimated age-1 abundance from the base operating model were ascribed to climate when estimating historical and generating future age-1 abundance in the climate

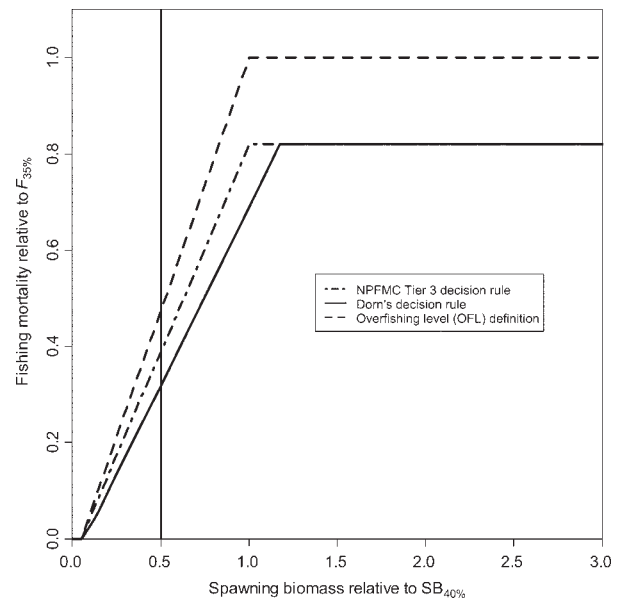


Figure 2. The OFL, the NPFMC Tier 3 upper bound of fishing mortality, and the upper bound of fishing mortality under the Dorn *et al.* (2001) control rule.

operating models; that is,

$$R_{y+1} = \bar{R}_1 \exp\left(\sum_{i=1}^n a_i I_{i,y}\right) \exp\left(\varepsilon_y - \frac{\sigma_R^2}{2}\right); \varepsilon_y \sim N(0, \sigma_R^2), \quad (1)$$

where \bar{R}_1 is the average level of age-1 abundance, ε_y the lognormal recruitment deviation for year y , σ_R the level of recruitment variability, “ $I_{i,y}$ ” the normalized seasonal climate indices, and “ a_i ” are the coefficients for the linear model of climate indices. The future seasonal climate indices from the IPCC datasets were normalized with the historical standard deviation and the mean of each future seasonal climate index for 2001–2005.

The value for σ_R , which was set to 1.0 by Dorn *et al.* (2005), was set to 0.6 for the purposes of this study, so that inclusion of the linear model of the seasonal climate indices in the operating models would account for some of the variation in age-1 abundance. A lower value for recruitment variability may be more appropriate for more complex and/or biologically motivated recruitment models (e.g. models that incorporate density-dependence, spawning biomass, autocorrelation, etc.; Haltuch *et al.*, in press).

More than 100 models based on subsets of the 12 seasonal climate indices were examined. The quality of the fit for each model to the data available for assessment purposes (catch, survey indices of abundance, catch age and length compositions,

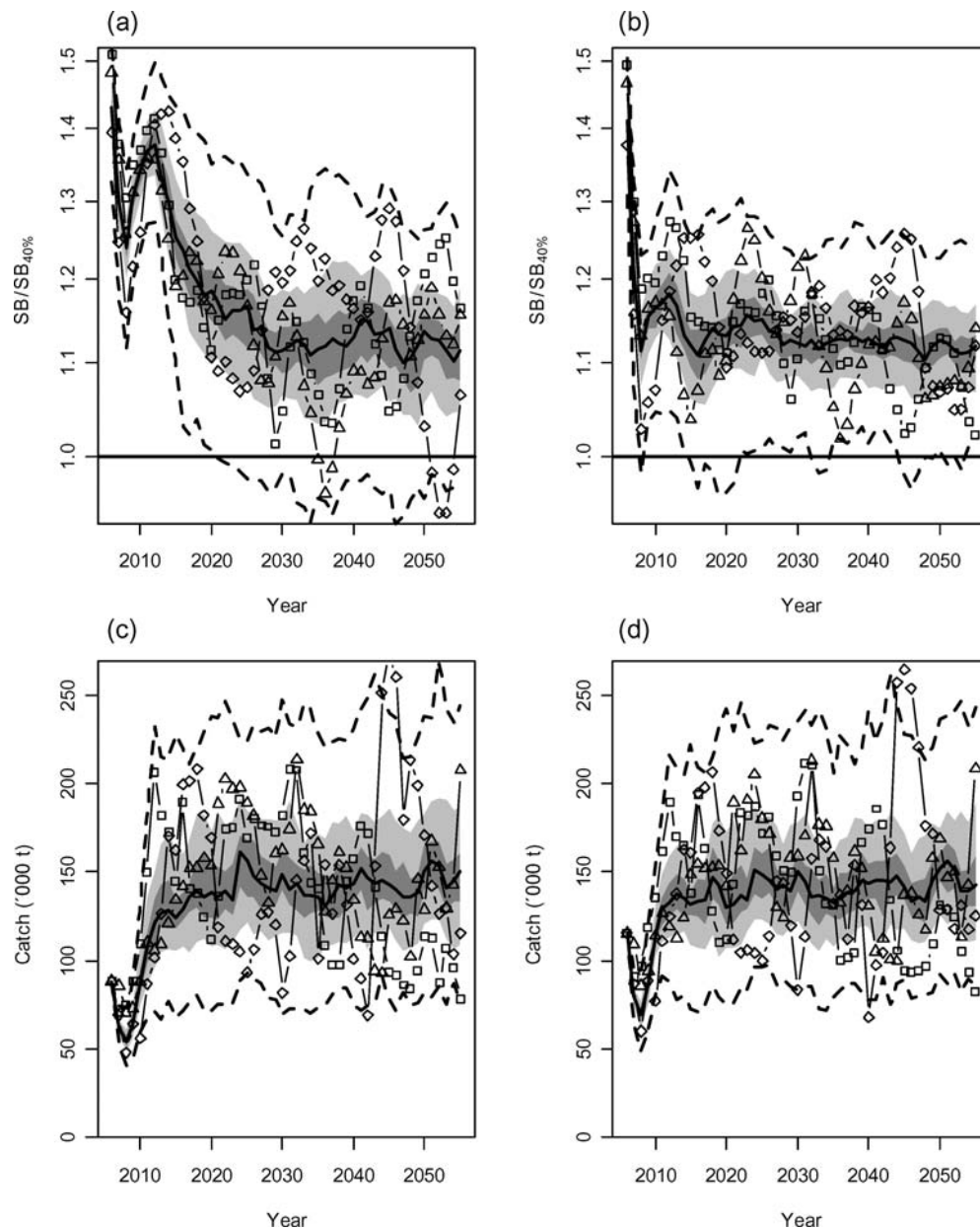


Figure 3. Time-trajectories for the current management strategy (left panels) and the dynamic B_0 management strategy (right panels) when there were no climate effects on recruitment: spawning biomass relative to the reference level $SB_{40\%}$ on a log scale (with three realizations of spawning biomass relative to $SB_{40\%}$, upper panels), and catch applied in thousands of tonnes (with three realizations of the catch applied, lower panels). For the envelopes, the solid black line is the median, the darker shaded area covers the 40th through the 60th percentiles, the lighter shaded area covers the 25th through the 75th percentiles, and the dashed lines are the 5th and 95th percentiles.

and survey age and length compositions) was compared with that of the base operating model, which does not include any climate indices, using Akaike's Information Criterion (AIC; Akaike, 1973). Cases where the MCMC algorithm obviously failed to converge were ignored. The base operating model (no climate indices) estimated 307 parameters (the average level of age-1 abundance, the average level of fishing mortality, catchability for the surveys, selectivity parameters for the fishery and the surveys, annual recruitment deviations, annual fishing mortality deviations, annual fishery selectivity deviations, and initial

deviations from the equilibrium age structure). Two operating models that included a linear combination of seasonal climate indices were selected for the MSE (Table 4, Appendix). Operating model 1 included winter precipitation, spring SST, summer precipitation, summer SST, and autumn SST. Operating model 2, which is nested within model 1, included winter precipitation, spring SST, summer SST, and autumn SST. These two models had the lowest values for AIC of all the models that included a linear combination of seasonal climate indices. All models that included a linear combination of

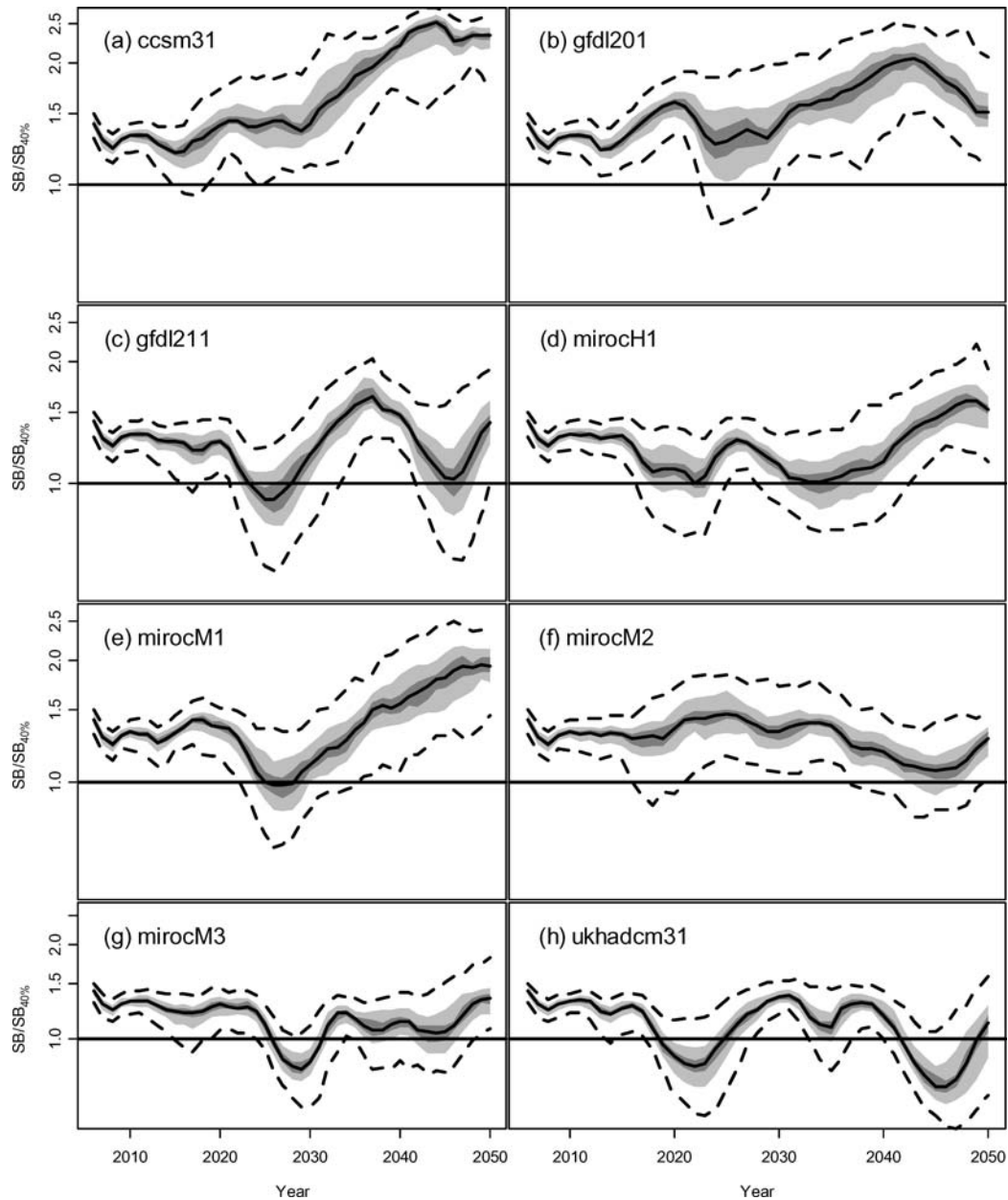


Figure 4. Time-trajectories of spawning biomass relative to the reference level $SB_{40\%}$ on a log scale under operating model 1 for the eight IPCC datasets when catch limits were based on the current management strategy. Lines and envelopes are as in Figure 3.

seasonal climate indices were preferred to the base model according to AIC.

The management strategy

The management strategy was the combination of a catch control rule (Figure 2) and a stock assessment (estimation) model that fitted an age-structured population dynamics model to fishery, survey, and biological data to produce estimates of the biological reference points $F_{40\%}$ (the fishing mortality that reduces the spawning biomass-per-recruit to 40% of the average unfished spawning biomass-per-recruit) and $SB_{47\%}$ (the spawning biomass associated with $F_{47\%}$) and the current spawning biomass, which were used in the control rule. The “Dorn rule” [Equation (2), with $\alpha = 0.05$; Figure 2] determines the upper

bound of fishing mortality, F_{ABC} , and hence the ABC:

$$F_{ABC} = \begin{cases} F_{40\%} & \text{if } SB/SB_{47\%} > 1 \\ F_{40\%}[(SB/SB_{47\%} - \alpha)/(1 - \alpha)] & \text{if } \alpha < SB/SB_{47\%} \leq 1 \\ 0 & \text{if } SB/SB_{47\%} \leq \alpha \end{cases} \quad (2)$$

The control rule also included an overfishing level (OFL) of fishing mortality (F_{OFL}), defined in terms of $F_{35\%}$ (which is used as a proxy for F_{MSY}). F_{OFL} is used to determine the OFL. If the fishing mortality exceeds F_{OFL} , “overfishing” as defined under the Magnuson–Stevens Fishery Conservation and Management Act (MSFCMA) is said to be occurring. A spawning biomass of 20% of the average unfished spawning biomass, $SB_{20\%}$, has been

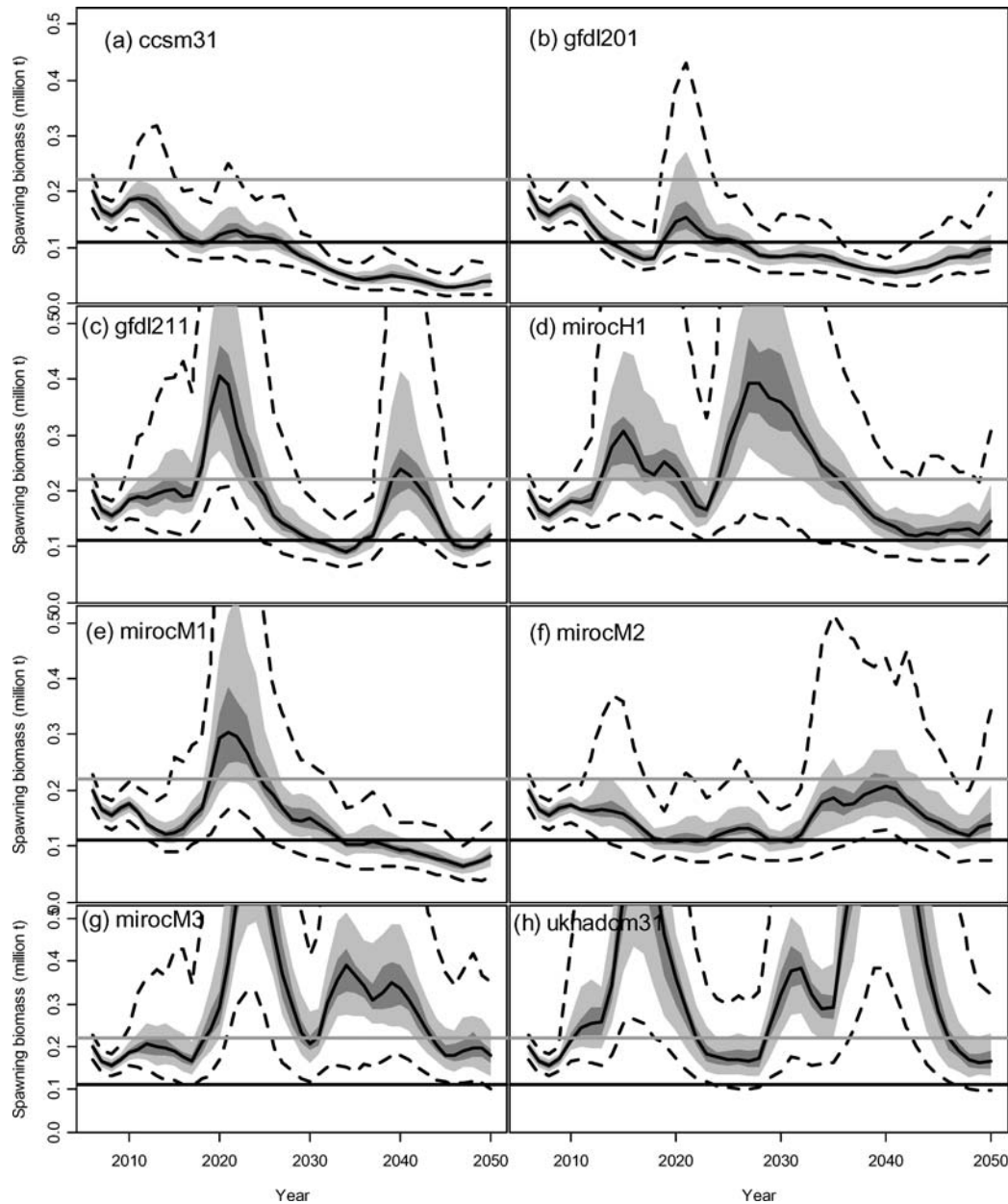


Figure 5. Time-trajectories of spawning biomass in millions of tonnes under operating model 1 for the eight IPCC datasets when catch limits were based on the current management strategy. The thick black horizontal lines indicate the 2006 value of $SB_{20\%}$ and the light grey horizontal lines indicate the 2006 value for $SB_{40\%}$ (Dorn *et al.*, 2006); others lines and envelopes are as in Figure 3.

established as a level below which no directed fishing would be allowed (the vertical line in Figure 2), as an additional precautionary measure to protect an endangered stock of Steller sea lions (*Eumetopias jubatus*), which consume walleye pollock.

Two management strategies were considered. Both defined the reference level of spawning biomass in year y , $SB_{47\%}(y)$, as the spawning biomass-per-recruit at $F_{47\%}$ multiplied by the average recruitment for year y :

$$SB_{47\%}(y) = SBPR(F_{47\%}) \bar{R}_y, \quad (3)$$

where $SBPR(F)$ is the spawning biomass-per-recruit when the fully selected fishing mortality equals F . The current management

strategy defined \bar{R}_y as the mean recruitment for year classes spawned between 1977 and year $y-1$:

$$\bar{R}_y = \frac{1}{(y-1979)} \sum_{u=1979}^{y-1} N_{u,2}, \quad (4)$$

where $N_{y,a}$ is the number of animals of age a at the start of year y . The dynamic B_0 management strategy defined \bar{R}_y as a weighted average of the past 25 years of age-2 abundance:

$$\bar{R}_y = \frac{\sum_{a=2}^{26} m_a w_a N_{y-a+1,2} \exp[-\sum_{b=2}^{a-1} M_b]}{\sum_{a=2}^{26} m_a w_a \exp[-\sum_{b=2}^{a-1} M_b]}, \quad (5)$$

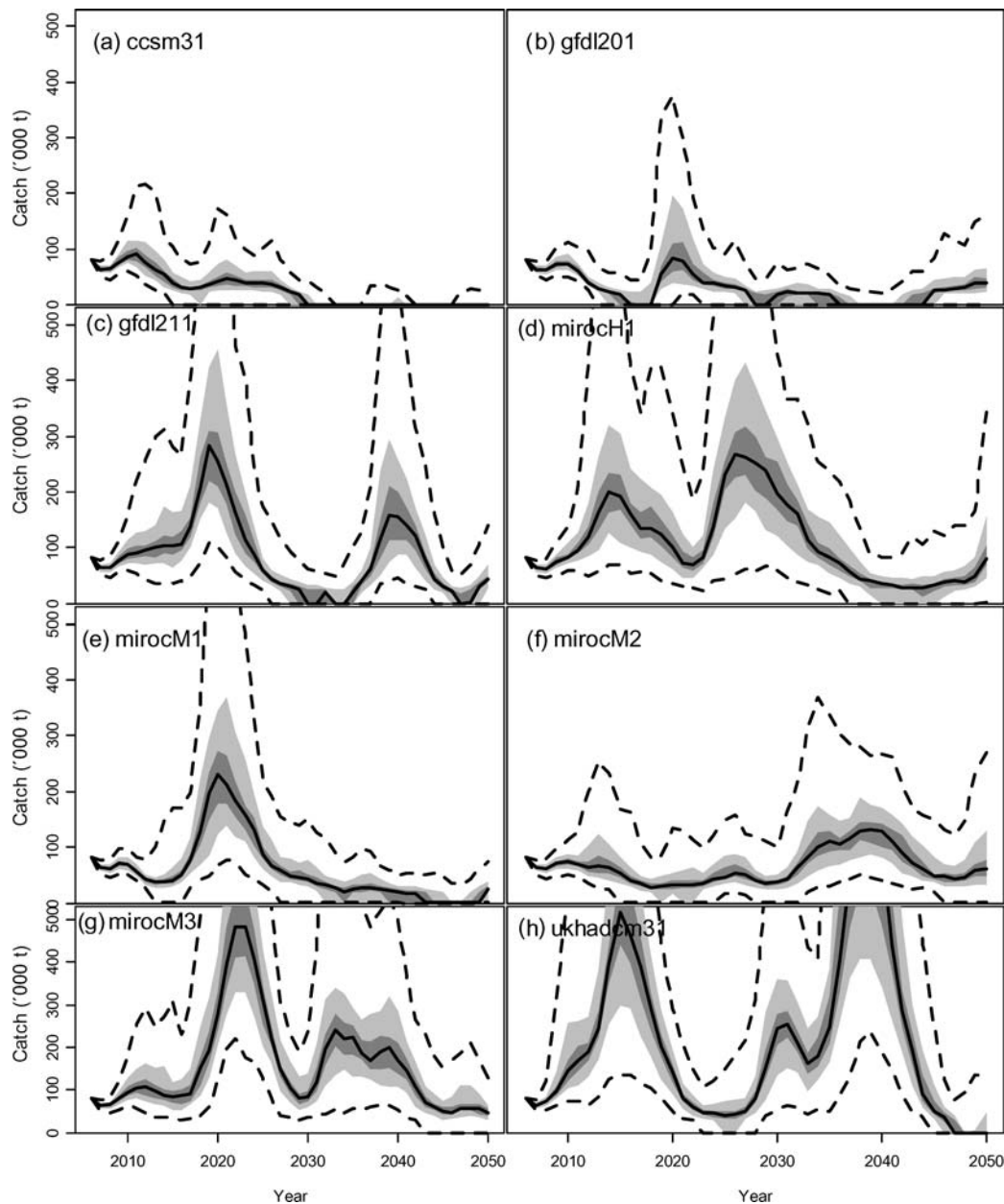


Figure 6. Time-trajectories of catch in thousands of metric tonnes under operating model 1 for the eight IPCC datasets when catch limits are based on the current management strategy. The lines and envelopes are as in Figure 3.

where m_a was the fraction of animals of age a that are mature, and w_a was the average mass of an animal of age a . The term dynamic B_0 refers to calculating the reference level of unfished equilibrium biomass, B_0 , under the prevailing environmental conditions (cf. MacCall *et al.*, 1985). This approach allows the average level of age-2 abundance on which management decisions are based to be much more responsive to prevailing conditions and to recruitment values based on their prevalence in the population and their contribution to spawning biomass.

Output statistics

The performance measures consisted of two types (estimation and management). The management performance measures were

selected based on the goals of the NPFMC (NPFMC, 2006) and the MSFCMA. They were the spawning biomass relative to the reference level $SB_{40\%}$, the probability that the spawning biomass fell below $SB_{20\%}$, the probability that the catch was higher than OFL, and the catch over the projection period.

The results of the simulations are displayed graphically for brevity. Specifically, the ability of the management strategy to leave the spawning biomass close to the reference level $SB_{40\%}$ and achieve high catches was summarized using plots of the following:

- (i) the distribution of the time-trajectory of the spawning biomass;

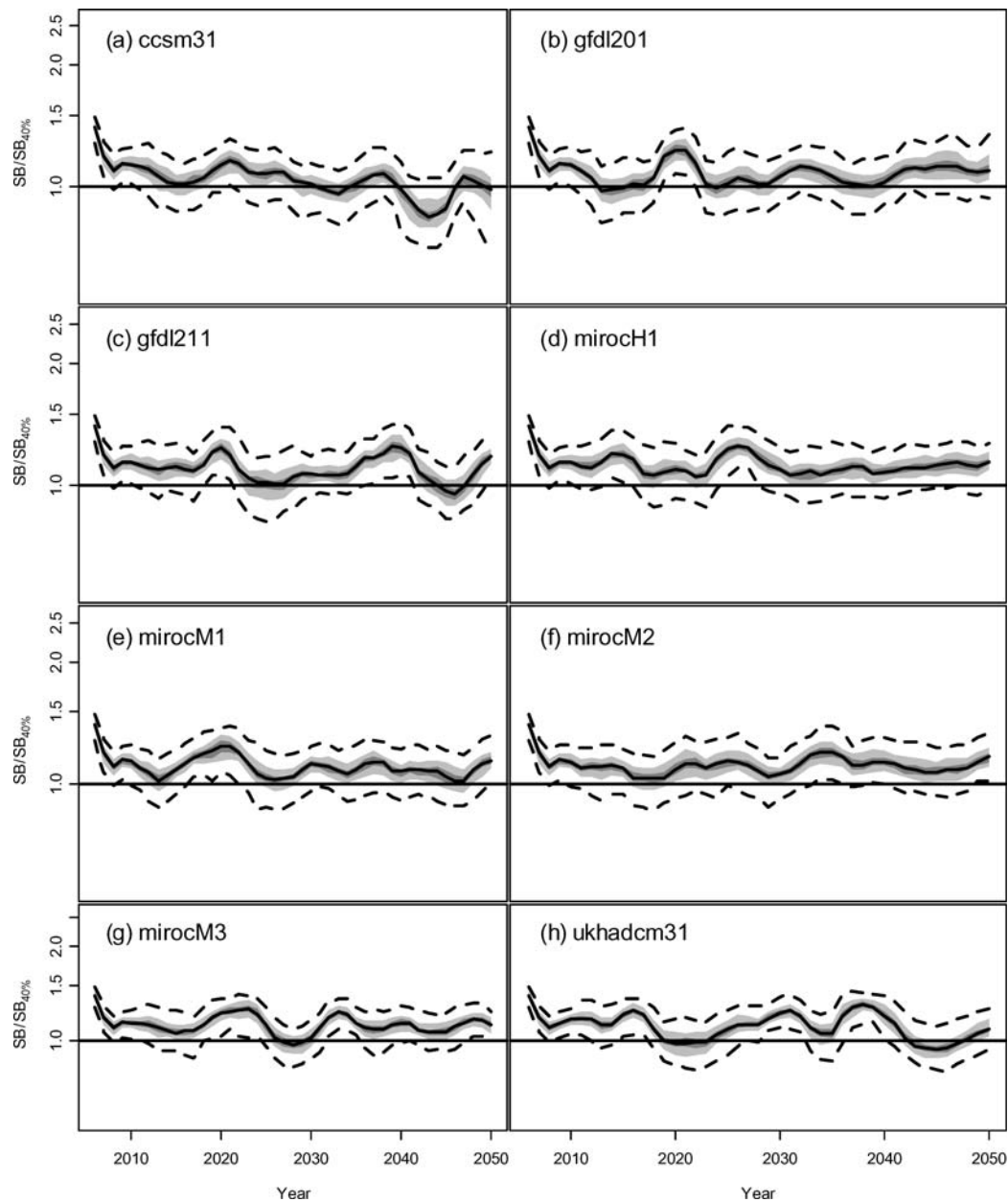


Figure 7. As for Figure 4, except that the results pertain to the dynamic B_0 management strategy.

- (ii) the distribution of the time-trajectory of the ratio of the spawning biomass to the reference level of $SB_{40\%}$;
- (iii) the distribution of the time-trajectory of annual catches.

The estimation performance measures are illustrated in plots of the distribution of the time-trajectory for the percentage relative errors of: (i) spawning biomass in the final year of the assessment period; (ii) fishing mortality in the final year of the assessment period; (iii) the reference level of spawning biomass, $SB_{40\%}$; and (iv) the ABC under the control rule. The assessment period was defined as 1961–2005 (the period of historical data) through year $y-1$ of the projection period for a stock assessment performed in year y . The operating model values for $SB_{40\%}$, $SB_{47\%}$, and the ABC were based on average age-1 recruitment, calculated using an appropriately modified version of Equation (5).

Results

The climate–recruitment models

The two operating models were selected from more than 100 candidate models using AIC, and included winter precipitation, spring SST, summer SST, and autumn SST. Operating model 1 also included summer precipitation. The signs of the model estimates for the coefficients for winter precipitation, spring SST, and autumn SST matched those expected from established hypotheses (compare Table 1 and Appendix); that is to say, GOA walleye pollock recruitment was estimated as negatively correlated with spring SST, and positively correlated with winter precipitation and summer SST. The model estimates of the coefficients for winter precipitation, spring SST, summer SST, and autumn SST were significant, in that none fell outside of the 95% asymptotic confidence interval for each

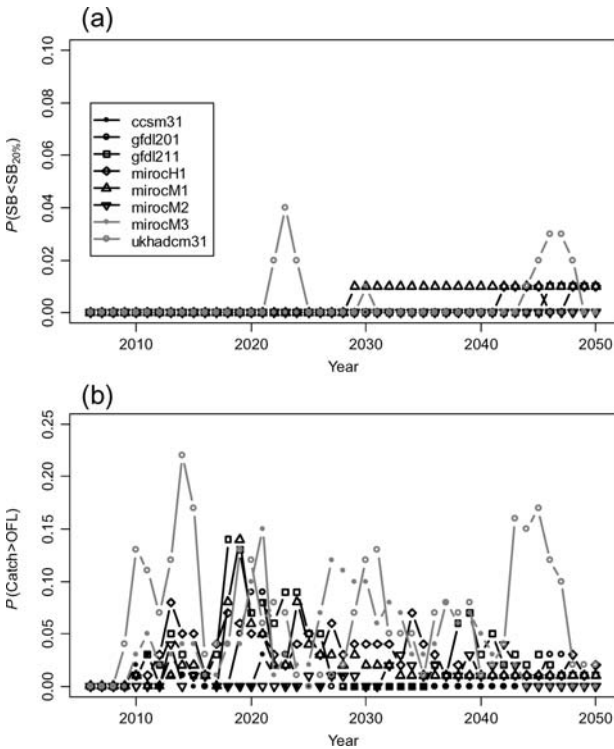


Figure 8. Probability of spawning biomass dropping below $SB_{20\%}$ (a) and the catch exceeding the OFL (b) for operating model 1 for the eight IPCC datasets when catch limits were based on the current management strategy.

coefficient. The specific mechanisms governing the effects of summer precipitation and autumn SST on the abundance of age-1 walleye pollock are, however, not evident from past work, but the selection of these covariates suggests that they

should be the focus for the development of new hypotheses. The climate models explained a substantial fraction of the variation in the estimates of age-1 recruitment. The standard deviation of recruitment about its expected value was 0.98 for the base operating model, 0.76 for operating model 1, and 0.78 for operating model 2.

Management performance

The management performance of the current and the dynamic B_0 management strategies was evaluated in terms of the spawning biomass relative to the reference level $SB_{40\%}$, and by the amount of and variation in catches. These two management strategies achieved average catches of 146 900 and 146 300 t (Figure 3) for 2015–2050, respectively, for the base operating model, where there was no effect of climate on age-1 abundance. Both strategies maintained spawning biomass above $SB_{40\%}$ over 90% of the simulations (Figure 3).

The performance of the current management strategy in terms of catches and future stock sizes depended on the choice of IPCC dataset (see Figures 4–6 for results for model 1). Although the time-trajectory of true spawning biomass relative to the true reference level $SB_{40\%}$ ($SB/SB_{40\%}$) was sensitive to which IPCC dataset was used to determine future recruitment in the operating model, stock size was kept above $SB_{40\%}$ between 69% (dataset ukhadcm31) and 98% (dataset ccsm31) of the 4500 year \times simulation combinations that constitute the projection period (Figure 4). Spawning biomass (Figure 5) varied more than $SB/SB_{40\%}$ because $SB_{40\%}$ changed over time as a function of expected age-1 abundance [Equation (3)], so variability (and trend) in spawning biomass was scaled out to some extent in Figure 4. The projections based on datasets ccsm31, gfdl201, and mirocM1 left the spawning biomass below the 2006 estimate of $SB_{40\%}$ (220 000 t; Dorn *et al.*, 2006) for most of the projection period, and even below the 2006 estimate of $SB_{20\%}$ for the latter part of the projection period. The spawning biomass was

Table 5. Minimum and maximum values over 2015–2050 of the median (over simulations) percentage relative errors for spawning biomass (SB), fishing mortality (F), $SB_{40\%}$, and ABC.

Scenario	Recruits ($\times 10^9$)	Current management strategy				“Dynamic B_0 ” management strategy			
		SB	F	$SB_{40\%}$	ABC	SB	F	$SB_{40\%}$	ABC
Base	1.565	−5.24	16.06	9.80	−5.59	−5.08	15.57	−0.48	−1.99
	1.190	−11.56	5.06	−6.69	−19.04	−11.19	5.31	−10.47	−14.97
ccsm31	1.224	3.87	6.18	100+	−37.79	−3.15	8.03	40.57	34.44
	0.015	−9.59	−25.40	63.18	−99.42	−14.01	−37.12	−14.72	−24.29
gfdl201	2.534	1.42	6.54	100+	−16.48	−1.08	10.96	33.52	11.52
	0.047	−10.20	−13.27	64.37	−99.37	−14.85	−14.34	−42.47	−27.23
gfdl211	4.536	4.30	15.97	100+	−0.24	7.53	20.19	36.11	7.36
	0.072	−11.54	−8.56	−30.17	−99.10	−13.00	−11.43	−49.21	−38.04
mirocH1	3.972	0.40	16.77	100+	−2.79	−0.28	16.74	25.47	1.33
	0.114	−13.13	−3.83	−29.61	−52.98	−13.58	−5.24	−29.01	−28.81
mirocM1	3.837	0.27	15.60	100+	−3.07	0.09	17.78	27.77	8.54
	0.054	−12.72	−10.09	−22.29	−99.34	−14.21	−12.28	−36.60	−30.50
mirocM2	1.866	−1.87	11.60	100+	−6.81	−2.43	12.62	22.50	0.22
	0.074	−10.57	−3.95	−8.68	−49.62	−12.04	−3.26	−26.19	−25.54
mirocM3	7.918	4.14	21.35	99.81	8.68	3.91	23.55	40.18	0.77
	0.070	−15.40	−1.35	−54.02	−44.92	−15.15	−1.99	−43.68	−43.01
ukhadcm31	13.312	7.65	27.95	99.08	9.77	7.99	31.87	53.35	2.77
	0.008	−18.61	−15.90	−64.73	−98.70	−16.50	−24.71	−47.03	−60.06

Values of 100+ indicate that the median relative errors concerned were at least 100%. Minimum and maximum values over 2015–2050 for the medians over simulations of age-1 abundance (recruits) are given for each scenario. The results in this table are based on operating model 1.

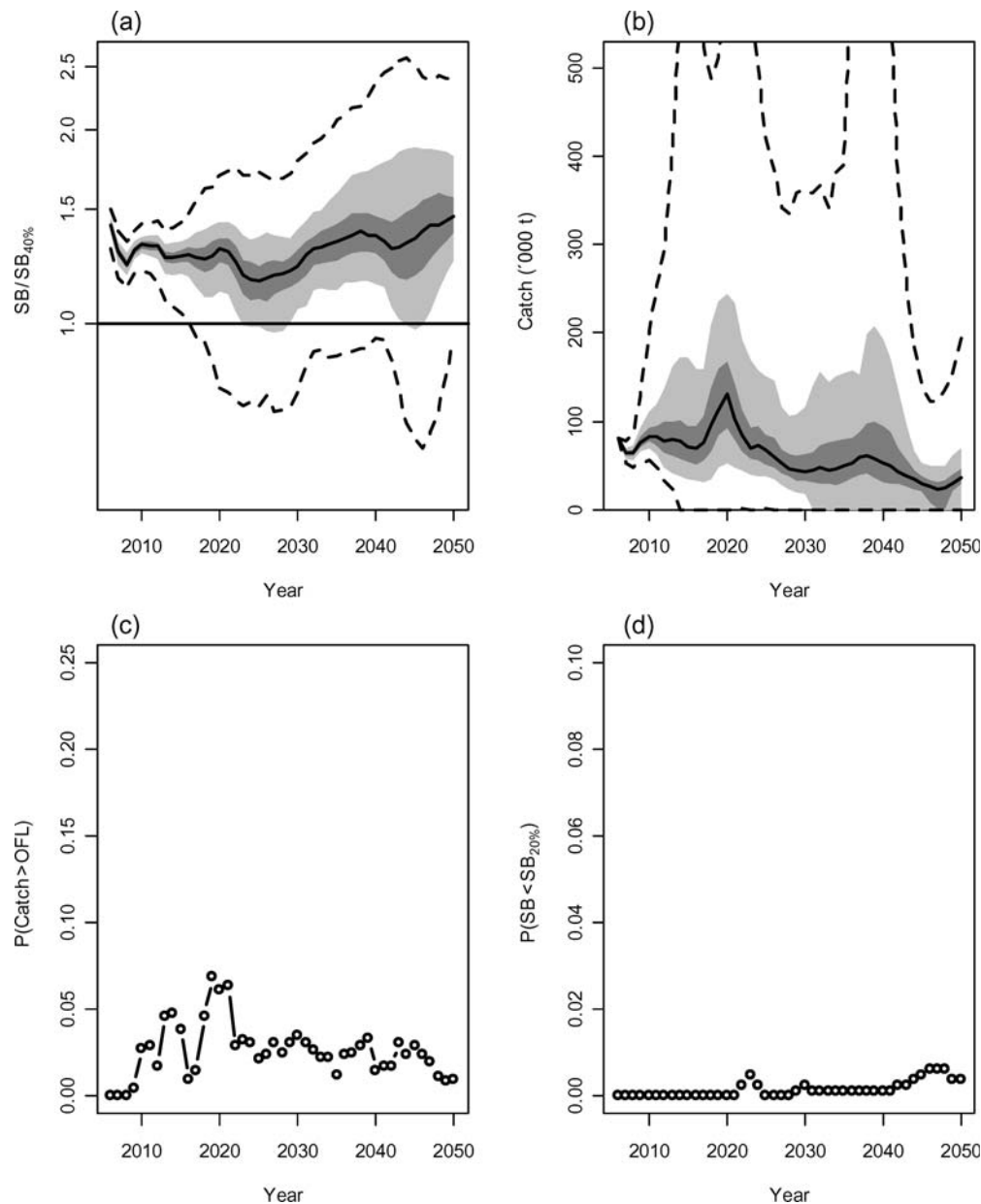


Figure 9. (a) Time-trajectories of spawning biomass relative to the reference level $SB_{40\%}$ on a log scale, (b) catch applied in thousands of tonnes, (c) the probability of the catch exceeding the OFL and, (d) the probability of spawning biomass dropping below $SB_{20\%}$ under operating model 1 for the combined results for the eight IPCC datasets when catch limits were based on the current management strategy. Lines and envelopes are as in Figure 3.

between the 2006 values for $SB_{20\%}$ and $SB_{40\%}$ for most of the projection period for dataset *mirocM2*. In contrast, the spawning biomass was generally substantially above these levels for the projections based on the remaining IPCC datasets.

The current and dynamic B_0 management strategies differed in that the definition of $SB_{40\%}$, because the latter was essentially the same as that of the operating model. The values for $SB/SB_{40\%}$ under the dynamic B_0 management strategy exhibited less inter-annual variation than those for the current management strategy (Figures 4 and 7), and $SB/SB_{40\%}$ was much closer to 1 for all IPCC datasets for the dynamic B_0 strategy. This management strategy also set higher catches during periods of low recruitment and vice versa.

Extreme results for operating model 1 occurred when age-1 abundance was driven by IPCC datasets *ccsm31* and *ukhadcm31*. The performance of the current and dynamic B_0 management strategies were qualitatively similar for operating models 1 and 2 for these datasets, because the results were largely insensitive to excluding summer precipitation when generating future age-1 abundance.

The time-trajectories of catch (Figure 6) exhibited the same patterns as those for spawning biomass, with higher variability at higher catch levels, although, as expected, catches were much lower when stock size was low owing to the threshold nature of the catch control rule [see Equation (2)]. The catches under the eight IPCC datasets were much more variable than those under

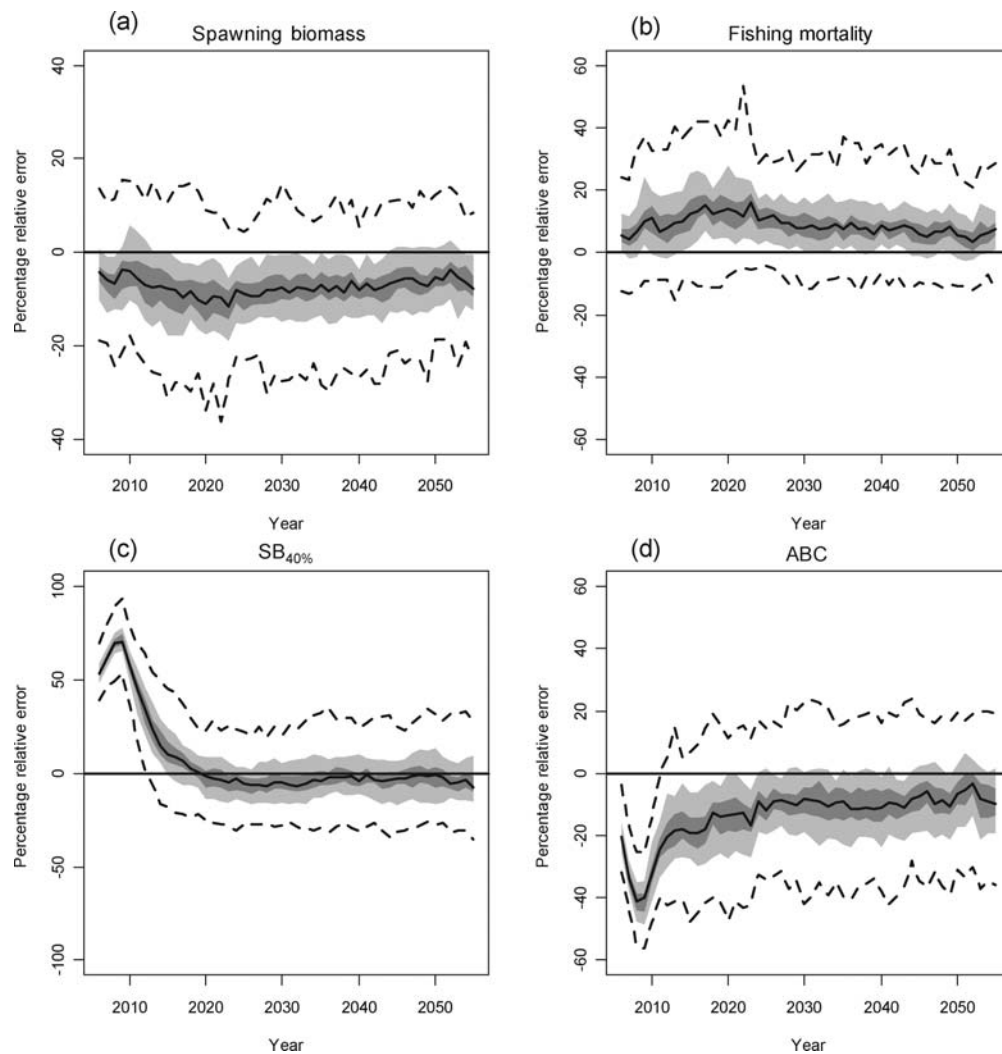


Figure 10. Estimation performance for the base operating model (no climate effects on recruitment) for the current management strategy: the distributions of percentage relative error between the estimated and “true” values for the most recent year of the assessments for (a) spawning biomass, (b) fishing mortality, (c) $SB_{40\%}$ and (d) ABC.

the base operating model (contrast Figures 3 and 6). The average annual catches for 2015–2050 under the climate scenarios for operating model 1 ranged from 18 000 to 314 000 t for the current management strategy and from 29 000 to 300 000 t for the dynamic B_0 management strategy (datasets ccs31 and ukhadcm31, respectively). For operating model 2, the average annual catches were 18 000 and 29 000 t for dataset ccs31, and 265 000 and 252 000 t for dataset ukhadcm31 (for the current and dynamic B_0 management strategies, respectively).

Figure 8 summarizes the performance of the current management strategy in terms of the probability of the spawning biomass dropping below the $SB_{20\%}$ [defined using Equation (5)] and the catch exceeding OFL. All IPCC datasets led to a probability of <0.05 of dropping below $SB_{20\%}$ (Figure 8a). Four of the IPCC datasets (gfdl211, mirocM1, mirocM3, and ukhadcm31) led to at least one period when $P(\text{Catch} > \text{OFL})$ was 0.10 or larger, with a maximum value for $P(\text{Catch} > \text{OFL})$ of <0.25 (Figure 8b). The average catches and the variation in catch for IPCC datasets ccs31, gfdl201, and mirocM2 were lower on average than those

for the other IPCC datasets (Figure 6), because the average age-1 abundance and variation in age-1 abundance for these datasets were lower than those for the other IPCC datasets (Table 5). The average (over simulations) coefficient of variations (CVs) of the future time-trajectories of age-1 abundance for datasets ccs31, gfdl201, and mirocM2 were 1.77, 1.91, and 1.55, respectively, substantially higher than the average CV for the base operating model (0.64). The average CVs of recruitment for the other IPCC datasets ranged from 1.73 to 2.58. The dynamic B_0 management strategy performed slightly better than the current management strategy in terms of the probability of the spawning biomass dropping below the $SB_{20\%}$, but overall, the patterns were similar to those for the current management strategy (results not illustrated). In contrast, the dynamic B_0 management strategy performed worse than the current management strategy in terms of $P(\text{Catch} > \text{OFL})$, because catches were higher during periods of lower productivity for the dynamic B_0 management strategy.

The probability of dropping below $SB_{20\%}$ was essentially zero for the base operating model for both management strategies,

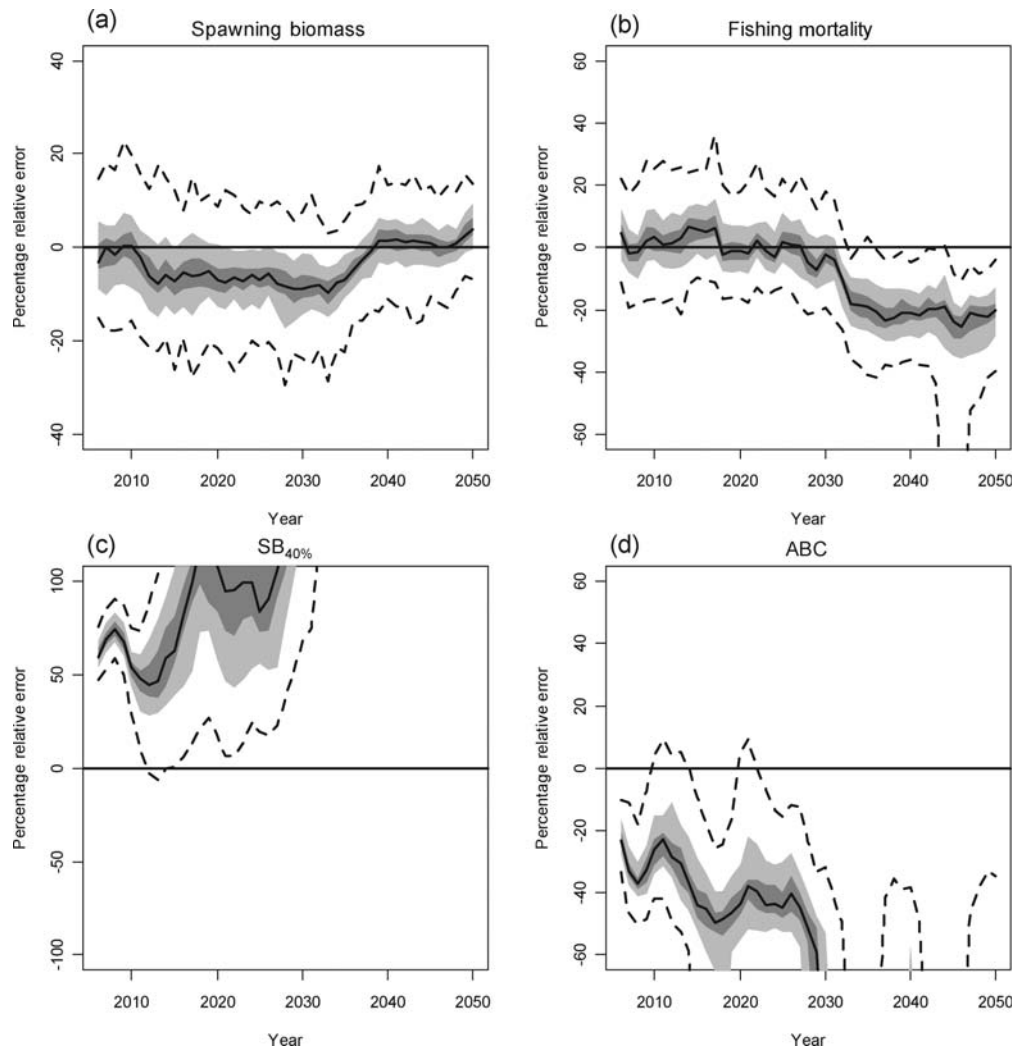


Figure 11. As for Figure 10, except that the results pertain to operating model 1 with IPCC dataset ccs31, and catch limits were based on the current management strategy.

whereas the maximum (over time) value of $P(\text{Catch} > \text{OFL})$ was 0.05 for the current management strategy and 0.12 for the dynamic B_0 management strategy for this operating model. These probabilities were higher for all IPCC datasets (Figure 8), indicating a higher probability of management failure, i.e. setting a non-zero ABC when stock size is below $\text{SB}_{20\%}$ or setting an ABC that leads to a catch greater than that mandated in the management plan, in the face of climate-induced fluctuations in walleye pollock recruitment.

An overall impression of management performance was achieved by pooling the results for the eight IPCC datasets over simulations. Figure 9 displays the integrated results for operating model 1 and the current management strategy. As expected, the integrated results exhibited less variation than those for the individual IPCC datasets did (contrast Figure 9 with Figures 4 and 6). However, there was still considerable interannual variation in biomass and catch. The probability of spawning biomass dropping below $\text{SB}_{20\%}$ was, as expected, higher for the integrated results than for the base operating model, whereas the probability of the catch exceeding the OFL was also somewhat higher than for the base operating model.

Estimation performance

The median (over simulations) percentage relative errors for the current management strategy and the base operating model were mild, generally 10% or less, with a negative bias for spawning biomass, $\text{SB}_{40\%}$, and ABC, and a positive bias for fishing mortality (Figure 10). A'mar *et al.* (2008) established that these biases are the result of differences between the operating model and the estimation model, in particular the age range each model covers, which leads to differences in selectivity for the fishery and the surveys.

In contrast, estimation errors were more serious when age-1 recruitment was driven by climate, specifically for $\text{SB}_{40\%}$ and ABC (e.g. the time-trajectories of relative error for IPCC datasets ccs31 and ukhadcm31 in Figures 11 and 12). Estimation performance was summarized by the minimum and maximum values of the median percentage relative errors for spawning biomass, fishing mortality, $\text{SB}_{40\%}$, and ABC over 2015–2050 (a period after which the median percentage relative errors in Figure 10 stabilized). Table 5 lists these minima and maxima for the base operating model, and when age-1 abundance was driven by climate according to operating model 1. The range of

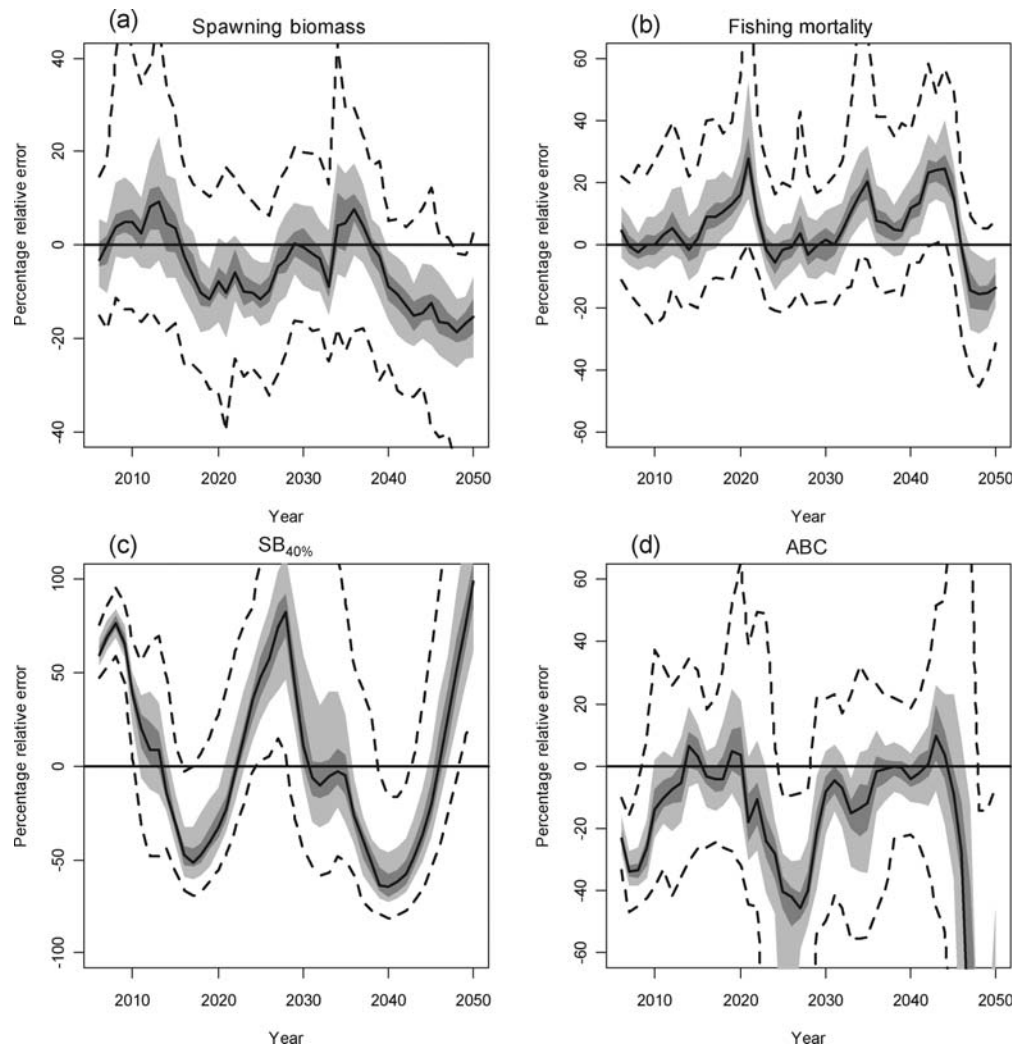


Figure 12. As for Figure 10, except that the results pertain to operating model 1 with IPCC dataset ukhadcm31, and catch limits were based on the current management strategy.

values in Table 5 is much wider when age-1 abundance was forced by climate than for the base operating model, and depended on the IPCC dataset (Table 5; Figures 11 and 12). The dynamic B_0 management strategy estimated $SB_{40\%}$ much better than the current management strategy did (results not presented), which is not surprising, because it is based on the correct definition for $SB_{40\%}$. Nevertheless, the errors when estimating ABC were high for both management strategies when recruitment was forced by climate (exceeding 50% often; Table 5).

The IPCC datasets with the largest ranges in median age-1 abundance (gfdl211, mirocM3, and ukhadcm31) led to the widest ranges in median percentage relative errors (Table 5), which suggests that one reason for the poorer estimation performance for the climate-based scenarios is that the assessment model was not able to detect large changes in recruitment quickly enough.

Discussion

The purpose of this study was twofold: (i) to examine the effect on the performance of the current management strategy of including seasonal climate indices as direct effects on age-1 abundance, and

(ii) to determine the relative performance of the current management and the dynamic B_0 management strategies as a function of which of the eight IPCC datasets was used to forecast future climate indices. Two operating models that included a relationship between climate indices and age-1 abundance of walleye pollock were considered. Both models included winter precipitation, spring SST, and summer SST, which are all associated with biological hypotheses regarding their effects on walleye pollock in the GOA in their first year.

The current management strategy kept the stock close to the reference level $SB_{40\%}$ on average. However, this management strategy allowed the stock to be reduced to very low levels (below the 2006 estimate of $SB_{20\%}$) under some climate scenarios. The dynamic B_0 management strategy kept spawning biomass closer to the reference level $SB_{40\%}$ and had a lesser probability of reducing the spawning biomass to below $SB_{20\%}$. However, the dynamic B_0 management strategy also had a higher probability of the catch exceeding the overfishing limit. The dynamic B_0 management strategy was based on the correct model for $SB_{40\%}$ and hence (potentially) had an unrealistic advantage over the current management strategy. Given this, and the results of this study, there

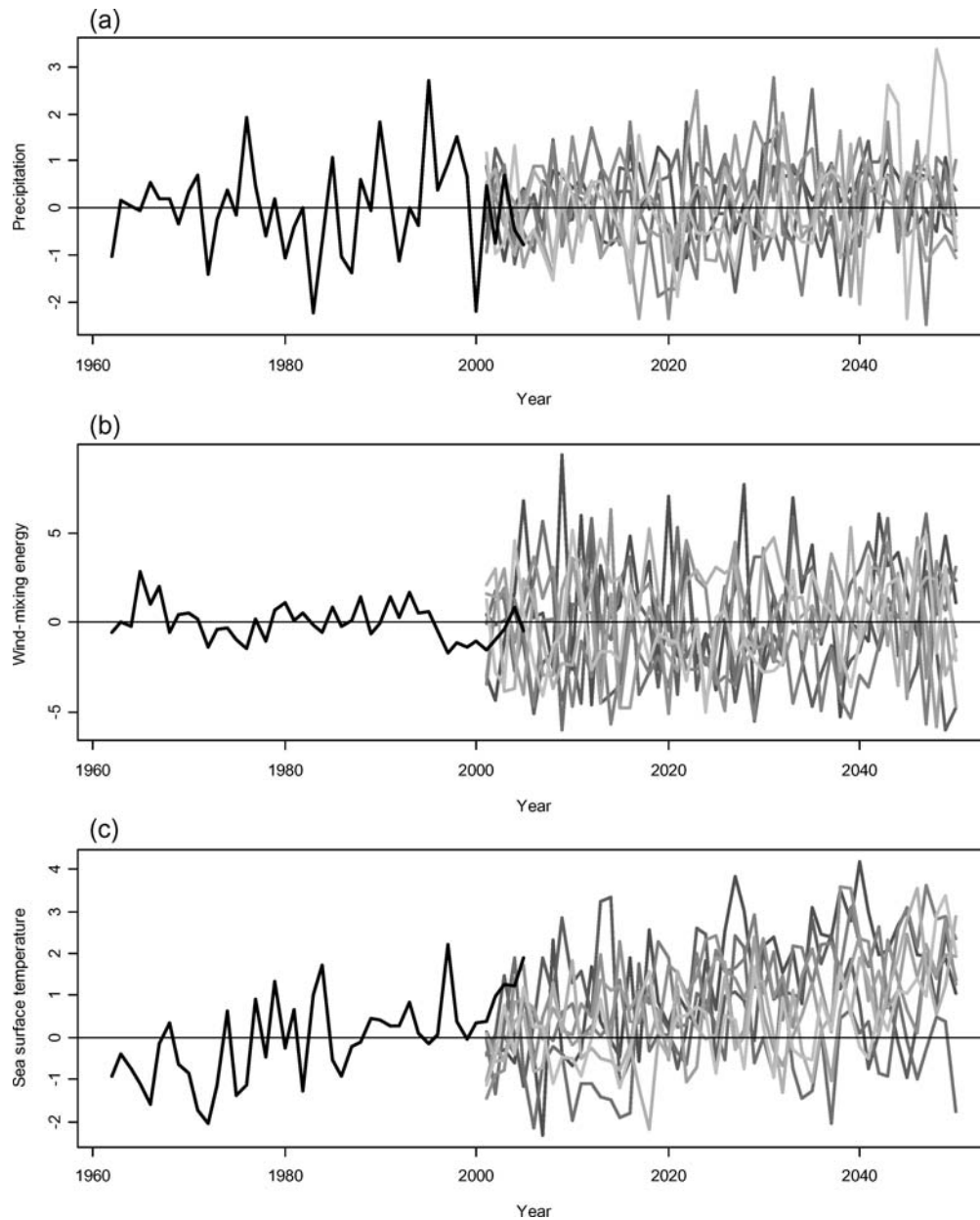


Figure 13. Time-trajectories of the normalized summer climate indices for the historical period (black line) and the eight IPCC datasets (grey lines) for (a) precipitation, (b) WME, and (c) SST.

seems little reason to advocate the dynamic B_0 management strategy.

The results varied considerably depending on which of the eight IPCC datasets was used to drive age-1 abundance, from low overall productivity for dataset ccs31 to large changes in productivity for dataset ukhadcm31. The main characteristics in the IPCC datasets were that average SST and variability in SST increased over the projection period (Figure 13c). The coefficients of the models for SST were generally negative, implying a declining trend over time in age-1 abundance (which is reflected in the spawning biomass trajectories in Figure 5).

Some of the simulations led to levels of recruitment that were outside of the historical range. In general, the trends in the environmental variables were such that recruitment was projected

to decrease over time. However, the environmental indices were predicted to be more variable into the future (in particular, WME; Figure 13b), which led to the possibility of recruitments that could exceed the historical levels of recruitment over the period 1976–2005. This extrapolation is undesirable in principle, but reflects the possibilities under future climate scenarios.

Both the current and the dynamic B_0 management strategies allowed spawning biomass to drop to low levels (even when scaled relative to $SB_{40\%}$, which accounts for changes over time in recruitment), because the management strategies were occasionally unable to respond sufficiently rapidly to trends in productivity. Further exploration of management strategies that combine aspects of both management strategies, as well as incorporate a fixed absolute limit above which the spawning biomass

must be maintained, may improve the performance of a management strategy for the GOA walleye pollock fishery with respect to changes and trends in productivity. In addition, the control rule defined by Equation (2) specifies the maximum fishing mortality rate, and hence ABC, at any given level of spawning biomass relative to $SB_{20\%}$. The analyses of this paper were based on the assumption that the catch limit was set to the ABC. Management performance, in terms of avoiding low stock size and high fishing mortality, would have improved had the catch limit been set below the ABC. In addition, there is no evidence of a stock–recruitment relationship for GOA walleye pollock (Dorn *et al.*, 2006; A'mar *et al.*, 2008), so there is currently no clear evidence of negative effects stemming from reducing spawning biomass to below the reference level.

The analyses of this study were based on forcing age-1 abundance using climate indices predicted from IPCC models, where relationships were characterized using historical climate indices when estimating age-1 abundance within stock-assessment-like operating models. Unlike most explorations of the effect of environmental factors on age-1 abundance, the parameters determining the relationship between climate indices and age-1 abundance were integrated into the operating model (*sensu* Maunder and Watters, 2003) and the projections accounted for the uncertainty in the coefficients for those relationships. In contrast, past use of the MSE approach to explore the effect of climate forcing on recruitment (Basson, 1999; Kell *et al.*, 2005; Hill *et al.*, 2006) was based on postulated relationships (IWC, 1993, 2003, 2005). The approach followed in this study allowed the data to identify the climate indices that were correlated with age-1 abundance, as well as the uncertainty associated with the relationships between age-1 abundance and climate.

There are several hypotheses about the effects of environmental forcing on the development and survival of GOA walleye pollock in their first year. Seasonal influences can act to enhance or impair survival, directly and indirectly, and in combination with other factors. Control rules and management strategies need to take the effects of climate change into account, so that stocks can be managed in a proactive and precautionary manner. This study indicates that the MSE approach can be used to explore the effects of some of these factors. The results of this study point to how alternative management strategies may be developed that are more robust to the effects of climate change than the current management strategy for GOA walleye pollock.

Finally, although this paper has focused on the effect of climate drivers on age-1 abundance, these are not the only factors that are likely to affect the dynamics of GOA walleye pollock and hence the performance of management strategies. Specifically, the GOA ecosystem has experienced major regime-shift events (Hare and Mantua, 2000) and (perhaps consequentially) changes in the sizes of fish and invertebrate complexes (NPFMC, 2007). The latter changes include major increases in the predation of GOA walleye pollock by fish predators, such as arrowtooth flounder (*Atheresthes stomias*; Gaichas, 2006). The MSE approach can be used to address each of these factors, which should lead to an ability to comment on which of these factors has the largest effect on the ability to achieve management goals for GOA walleye pollock.

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Appendix: Parameter estimates, standard deviations, and correlations

Base scenario operating model

Parameter	Estimate	s.d.	$\log(R_1)$	Winter precip	Spring SST	Summer precip	Summer SST	Autumn SST
$\log(R_1)$	20.870	0.057						
Operating model 1								
$\log(R_1)$	20.870	0.059	1.0					
Winter precip	0.339	0.119	-0.1353	1.0				
Spring SST	-0.833	0.180	0.1039	-0.3197	1.0			
Summer precip	-0.140	0.095	-0.0383	-0.1688	0.2164	1.0		
Summer SST	0.570	0.187	-0.0525	0.1758	-0.7516	-0.1409	1.0	
Autumn SST	-0.405	0.130	-0.1368	-0.3642	0.0458	0.0572	-0.3502	1.0
Operating model 2								
Winter precip	0.310	0.117	-0.1446	1.0				
Spring SST	-0.776	0.176	0.1156	-0.2945	1.0			
Summer SST	0.531	0.185	-0.0590	0.1560	-0.7462		1.0	
Autumn SST	-0.394	0.130	-0.1350	-0.3600	0.0338		-0.3457	1.0

The emboldened values indicate correlations >0.5 in absolute terms. "Precip" is precipitation and "SST" is sea surface temperature.